RESEARCH ARTICLE

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Comparative Simulation of Kalman Filter and Moving Average on Siemens S7-1200 PLC-Based Loadcell Sensor Readings

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Abstract

This work compared the effectiveness of the Kalman Filter and Moving Average Filter methods in minimizing noise and improving the stability of signal readings on a load-cell sensor simulation. The two filtering methods were applied to process the sensor data, to enhance both the precision and stability of the signal readings. According to the test results, the Kalman filter produced a lower average error of 0.0236, compared to 0.0244 when no filter was used, demonstrating its strong ability to reduce noise and signal fluctuations. On the other hand, the Moving Average Filter recorded a slightly higher error of 0.0238. Although it effectively smooths the signal, its performance is less reliable when dealing with higher levels of interference. Based on these findings, the Kalman Filter is considered more suitable for applications that require highly accurate and stable measurements, while the Moving Average Filter may be sufficient for environments with minimal noise.

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1 Introduction

In industrial control systems, accuracy and consistency of analog signal measurements are essential, especially when working with analog input devices. A common example used in load detection is the load cell sensor, which operates by translating variations in pressure into electrical signals that can be quantified [1]. These sensors are widely used in a variety of areas, including industrial weighing systems, automated processes, and quality assurance. To ensure the framework of sensor-based measurement, maintain both signal precision and consistency of the signal to be accurate and stable during operation to generate reliable data. However, the resulting signal often fluctuates due to external factors, such as noise.

In this case, the signal fluctuations that occur can reduce the effectiveness of the control system, so it is important to apply a filter method that can increase the stability of the signal reading. Thus, several filtering approaches can be applied to improve the accuracy

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of the readings and minimize noise, such as in the research conducted by Fambudi et al. [6] to study the application of a Kalman filter for the readings of the load cell sensor based on Siemens S7-1200 PLC. The research shows that the Kalman filter successfully reduces noise and increases the stability of the data from the load cell sensor by optimizing the Q and R values by observation first to get the right Q and R values. The Kalman filter method has a very wide application in various sensor applications to improve reading accuracy and reduce noise. As in Zhang's paper [10], the article discusses the application of the Kalman filter to improve the accuracy of very precise temperature measurements in applications for temperature measurements on spacecraft. This research shows that the Kalman filter can improve the resolution of temperature measurements much better than the initial measurement. In addition, there is research that uses a different filter method, namely moving average. Chalifatullah et al. [5] implements the moving average and Kalman filter on the wireless odometer for information on motor vehicle service. Moving Average Filter (MAF) is applied to reduce the noise that occurs in accelerometer sensor readings. The tests show that the MAF can smooth the data and reduce measurement errors caused by mechanical and electrical disturbances, with an average error of 1.81% in distance measurements. Although MAF successfully reduces noise, the results are still better using the Kalman filter, which gives a smaller error of 0.80%. Several previous studies have shown the application of filtering methods such as the Kalman filter and moving average filter in various sensor applications. Although not specific to load cell sensors, these methods can be applied to improve the stability of sensor readings, minimize noise, and produce more accurate data.

According to the aforementioned literature review, this research aims to apply and compare the Kalman and moving average filter methods to minimize noise in load cell sensor readings. These two methods will be compared in terms of their effectiveness in reducing signal fluctuations that can affect the accuracy of the readings.

2 Related Work

This study implements an experiment that integrates hardware and software. Therefore, this section will discuss a detailed explanation of the hardware used, including the Programmable Logic Controller (PLC) and load cell sensor components. In the following subsection, a detailed explanation of the software will be provided, focusing specifically on the algorithms, including the Kalman filter and the moving average filter.

2.1 Programmable Logic Controller (PLC)

The Siemens S7-1200 PLC is an industrial control apparatus utilized for the automation and regulation of various processes within a system. A PLC serves as an intermediary between the input and output devices by receiving signals from the input devices, such as sensors, switches, or buttons. This signal may manifest itself as a voltage, current, or digital signal. The PLC subsequently processes the incoming signals in accordance with a predetermined set of instructions articulated in a specific programming language, such as a ladder diagram (LD), structured text diagram (ST), or function block diagram (FBD). The PLC utilizes this software to determine the processing of input data for the operation of output devices, including motors and other actuators [2]. Figure 1 illustrates the physical appearance of the PLC used in this study.

Figure 1. PLC Siemens S7-1200 [6].

For this experiment, the Siemens Simatic S7-1200 CPU 1214C DC/DC/Rly was employed to acquire readings from the loadcell sensor. The selection of this PLC is based on its ability to convert and handle analog signals, allowing further processing and analysis. Detailed specifications for the PLC are provided in Table 1.

Table 1. The specification of PLC Siemens S7-1200.

Parameter	Description
Type	SIMANTIC S7-1200
Supply Voltage	24V DC
Load Voltage	24V DC
Input Current	500mA
Output Current	1600mA; Max. 5V DC for SM and CM

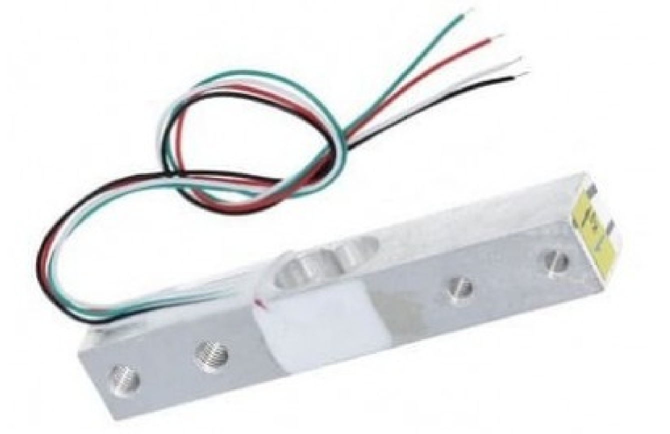

Figure 2. Load cell sensor.

2.2 Load cell sensor

A load cell sensor is a device that is used to measure the force or load by converting mechanical changes, such as pressure or force, into a measurable electrical signal [3]. Its operating principle is based on a strain gauge, a component that detects deformation or mechanical stress in a material when subjected to a load. When the load cell is given a load or force, the material inside will change shape, causing a change in resistance in the strain gauge. This resistance change is then converted into an electrical signal, which can be interpreted to calculate the magnitude of the applied load [7]. In this way, the load cell can provide measurement results. These sensors have found extensive use in a range of applications, including in weighing systems in industry, automation, and quality control [9]. In practical applications, the readings of the load cell sensor can be affected by external factors such as mechanical vibrations, electromagnetic interference, or fluctuation of the power supply. Similar vibration-induced noise has been effectively reduced using moving average filters in embedded systems [7]. These issues may compromise both the accuracy and stability of measurements in control systems. Therefore, a filtering method is applied in order to minimize the noise of the load cell sensor readings. The load cell sensor utilized in this work is depicted in Figure 2.

3 Methodology

A load cell sensor is employed and connected to a Siemens S7-1200 PLC, which serves to capture and convert analog input signals into digital data. The data obtained are subsequently evaluated to assess the efficacy of the two filtering techniques, specifically the Kalman Filter and the Moving Average Filter, in enhancing the stability of the signal output. In this section, we will provide a more in-depth explanation of both methodologies utilized in the software project.

3.1 Kalman Filter

The Kalman Filter is an algorithm commonly used to generate predictions of future values with reference to previous values. This method operates through two primary stages: prediction and correction. Initially, the filter generates an initial estimate based on the system model and existing data. This estimate is then refined during the correction phase using new data incoming from the measurement [8]. These two processes are mathematically represented by the following key equations. In the prediction stage, (1) was used to define the prediction of the state, and to calculate the prediction value of covariance, we can use (2). Meanwhile, (3), (4), and (5) are calculations to find the Kalman gain, the State Update, and the Covariance Update, respectively.

$$\widehat{x}_{k|k-1} = \widehat{x}_{k-1|k-1} \tag{1}$$

$$P_{k|k-1} = P_{k-1|k-1} + Q \tag{2}$$

$$K_k = P_{k|k-1}(P_{k|k-1} + R_k)^{-1} \tag{3}$$

$$\widehat{x}_{k|k} = \widehat{x}_{k|k-1} + K_k(y_k - \widehat{x}_{k|k-1}) \tag{4}$$

$$P_k = (1 - K_k)P_{k|k-1} \tag{5}$$

In this context, x denotes the state variable, P represents the covariance matrix of the state, Q is the matrix that describes the process noise, H serves as the measurement matrix, y indicates the observed measurement, R refers to the covariance of the measurement noise, and K stands for the Kalman gain. Figure 3 shows the Kalman filter flow chart for load cell data processing.

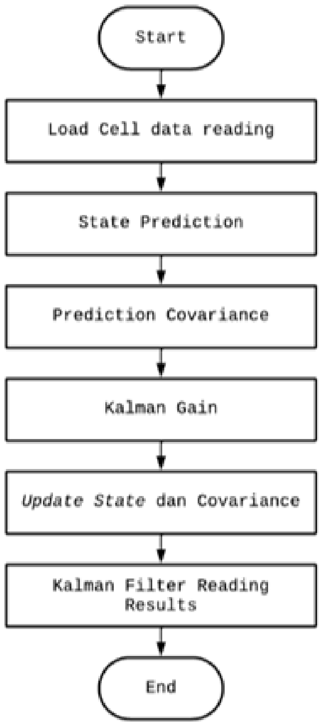

Figure 3. Kalman Filter process.

3.2 Moving Average Filter

The moving average is a filtering technique employed to smooth and refine data by computing the average of a set of values over a specified time interval [4]. This filter operates by shifting a data window and calculating the average when new data are introduced, thus facilitating the computation of a new average and aiding in noise reduction [9]. The moving average formula is delineated as follows:

$$\mu_m = \frac{\sum_{i=1}^{n} x_i}{n} \tag{6}$$

From equation (6), it can be seen that μ_m is the average result of the last n data used in each data shift. Each time the calculation is performed, taking data from points i, i-1, i-2,…, i-n+1. Over time, the calculation window moves one point forward, replacing old data with new data. Figure 4 shows the moving average filter flowchart for load cell data processing as follows:

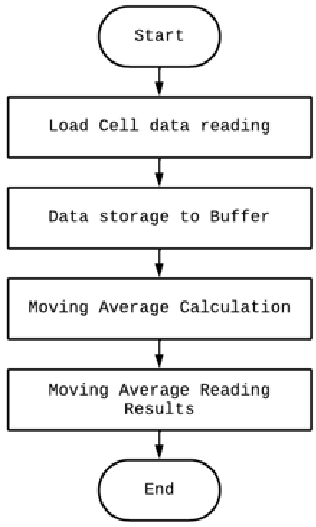

Figure 4. The flowchart of the mean average filter.

4 Experiments

This section examines the results of a simulation experiment that compares the Kalman filter and moving average filter methods using Matlab software. The test data was acquired from a load cell connected to a PLC S7-1200.

4.1 Data Acquisition

System testing is carried out as a process to obtain data from the readings of the load cell sensor. Data are obtained by connecting the load cell sensor to a Siemens S7-1200 PLC using the ladder programming language for sensor readings. In this process, the NORM_X and SCALE_X functions are used to normalize and adjust the range of input values received by the sensor, as shown in Figure 5.

The data obtained from ladder programming are the result of sensor readings. Figure 6 shows a sample graph of the load cell sensor readings used in this research as a simulation.

From the graph in Figure 6, the x-axis is the data index, which represents the time or the measurement sequence, while the y-axis is the voltage (V) generated by the load cell sensor. The measurement signal has a fairly variable voltage fluctuation; some parts show larger and smaller changes. Fluctuating sensor readings indicate the presence of external disturbances such as noise, which can affect the stability of the resulting signal. In this case, the application of filtering methods can be carried out for further analysis.

4.2 Evaluation of Kalman Filter

Floating sensor readings indicate the presence of external disturbances, such as noise, which can affect the stability of the resulting signal. So, the Kalman filter method is applied to improve and estimate the reading data of the load cell sensor. In its application, Kalman filter observation needs to be done first in order to know the right Q and R values. Two important parameters, namely the process covariance (Q) and

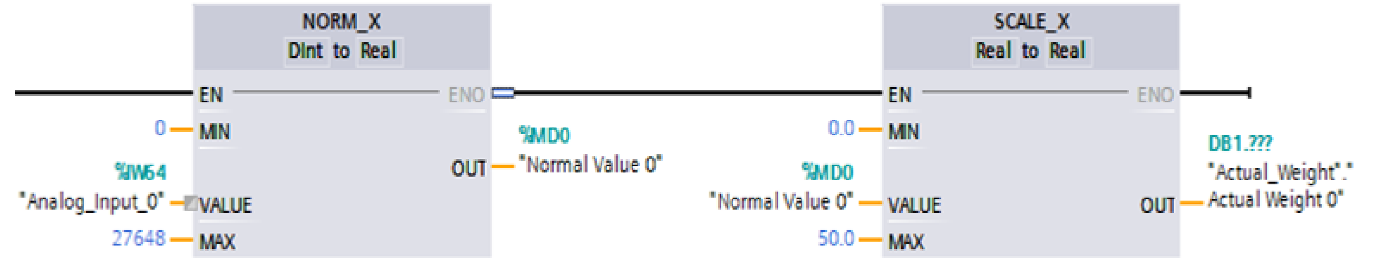

Figure 5. Norm_X and Scale_X ladder diagram.

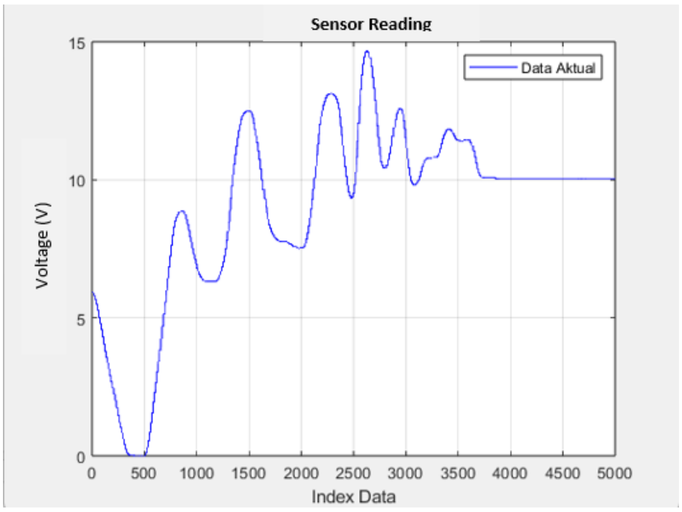

Figure 6. Sample sensor readings.

Algorithm 1: Kalman Filter Algorithm for Load Cell Sensor Data Processing

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Data: Sensor measurements array of length N
Result: Filtered sensor signal x_filtered
`// Initialize Kalman Filter (with no prior information)`
x_est ← 0;
; `// Initial state estimate`
P_est ← 1;
; `// Initial estimation uncertainty`
`// Set parameters (optimized via MATLAB analysis)`
Q ← 1;
; `// Process covariance`
R ← 10;
; `// Measurement noise covariance`
x_filtered ← zeros(N, 1);
for $i \leftarrow 1$ **to** N **do**
    `// Prediction step (time update)`
    x_pred ← x_est;
    P_pred ← P_est + Q;
    `// Update step (measurement update)`
    v_k ← measurements[i];
    ; `// Noisy sensor reading`
    s_k ← P_pred + R;
    K ← P_pred / s_k;
    ; `// Kalman gain`
    x_est ← x_pred + K × (v_k - x_pred);
    ; `// State update`
    P_est ← (1 - K) × P_pred;
    ; `// Covariance update`
    x_filtered[i] ← x_est;
    ; `// Store filtered value`
end

---

noise covariance (R), are determined by observation using the original reading value, which is then entered into software such as MATLAB for analysis and adjustment of the optimal Q and R values.

The initial initialization of the Kalman Filter begins with giving the values x = 0 and P = 1. The x-value initialized with 0 describes the initial estimate without information, while the P-value initialized with 1 describes the initial uncertainty assumed in the estimate. Then these values are entered into the Kalman Filter calculation, as shown in Algorithm 1.

The findings of the initial observations of the Kalman filter test are presented in Figure 7, with parameters Q=1 and R=10. This indicates that the Kalman filter closely approximates the actual data, as the readings of the actual data and the filter output are nearly identical.

The outcomes of the subsequent observation are illustrated in Figure 8, with Q=1 and R=100. The Kalman estimate appears smoother; however, it is somewhat divergent from the actual data.

Figure 9 displays the results of the Kalman filter test, which was performed using the parameter configuration Q=1 and R=1000. It can be seen from the graph that the filter gradually smoothes out the actual data and that the Kalman estimation results grow flatter. This is the case despite the fact that the filter value reading is increasingly away from the value

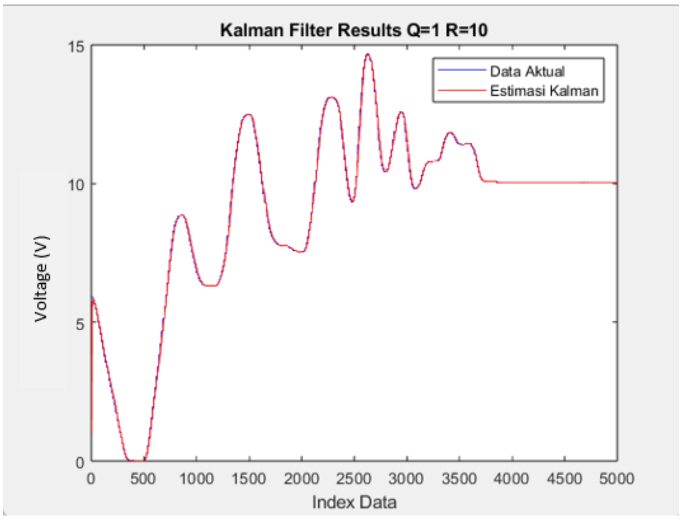

Figure 7. Kalman Filter results with Q = 1 and R = 10.

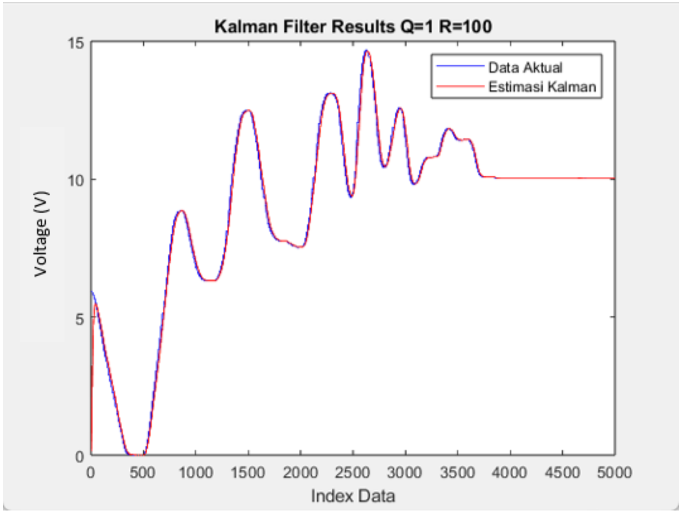

Figure 8. Kalman Filter results with Q = 1 and R = 100.

of the sensor data that was first collected.

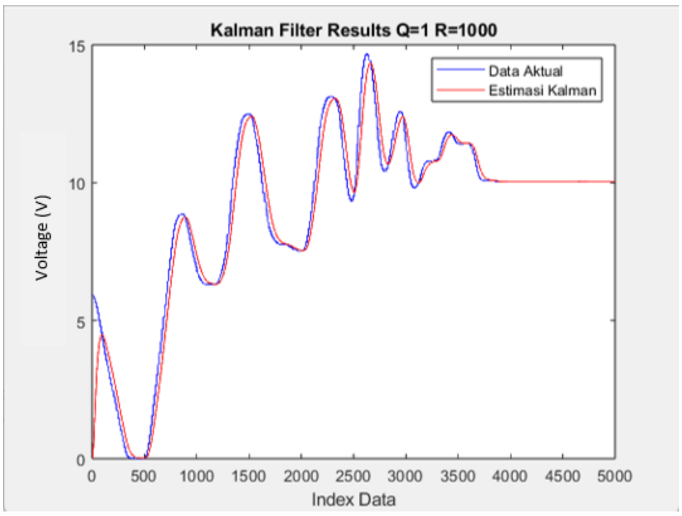

Figure 9. Kalman Filter results with Q = 1 and R = 1000.

According to the evaluation graphs that were presented before, it is known that the values of Q = 1 and R = 100 produce the best possible outcomes when the Kalman Filter is applied. It is possible for the filter to generate estimates that are smoother and more stable using these observation values. These estimates are closer to the actual data without over-smoothing the signal or moving away from the value that was initially detected by the sensor. In the meantime, the values of Q = 1 and R = 10 are extremely sensitive to even the smallest amount of noise. On the other hand, the values of Q = 1 and R = 1000 lead the filter to smooth the data to an excessive degree, which causes the filter to move further away from the actual data. It may be concluded that the parameters Q = 1 and R = 100 are the most effective ones for creating accurate and reliable readings in the field of sensor signal processing.

4.3 Evaluation of Moving Average Filter

The moving average filter technique is utilized to reduce load cell sensor reading data by employing a sliding window of preceding data points to compute the average. With each influx of fresh data, the window is adjusted to compute a revised average. The data is subsequently input into MATLAB software for analysis and window size modification. The software code for this method is presented in Algorithm 2.

Figure 10 illustrates the evaluation results of the mean average filter approach utilizing a window size of 5, yielding low attenuation of data variations. Despite the signal's increased smoothness, data fluctuations remain distinctly observable.

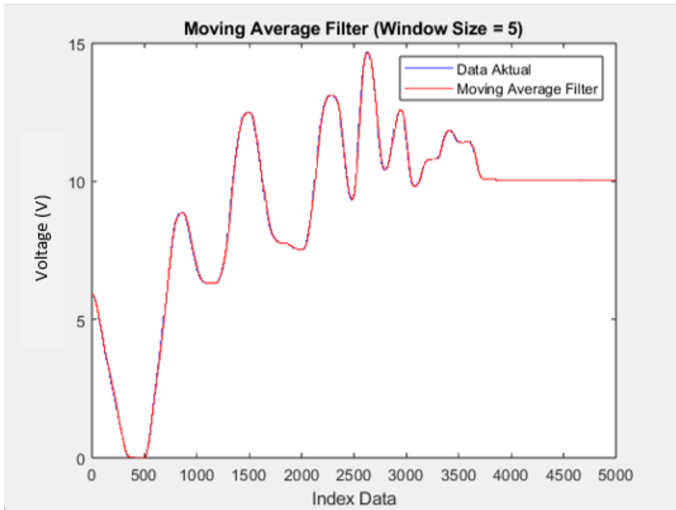

Figure 10. Moving Average result with Window Size=5.

Meanwhile, Figure 11 demonstrates the outcomes of the simulation test for the mean average filter

Algorithm 2: Moving Average Filter Algorithm for Sensor Data Smoothing

```
Data: Raw sensor measurements array of length N
Result: Filtered sensor signal x_filtered
Input: Window size M (determined via MATLAB
       analysis)
// Initialize with optimal window size
   (empirically determined as 50)
M ← 50 ;   // Optimal window size for balance
 between smoothing and accuracy
// Alternative window sizes tested:  M=5
   (light smoothing), M=20 (moderate), M=100+
   (excessive smoothing)
x_filtered ← zeros(N, 1);
for i ← 1 to N do
   // Handle initial phase when insufficient
      data points available
   if i < M then
      x_filtered[i] ← mean(measurements[1:i]);
      ;              // Use all available data
   end
   // Apply moving average with full window
      once sufficient data collected
   else
      // Extract the most recent M
         measurements for averaging
      window_data ← measurements[i-M+1:i];
      x_filtered[i] ← mean(window_data);
      ;              // Compute moving average
   end
end
```

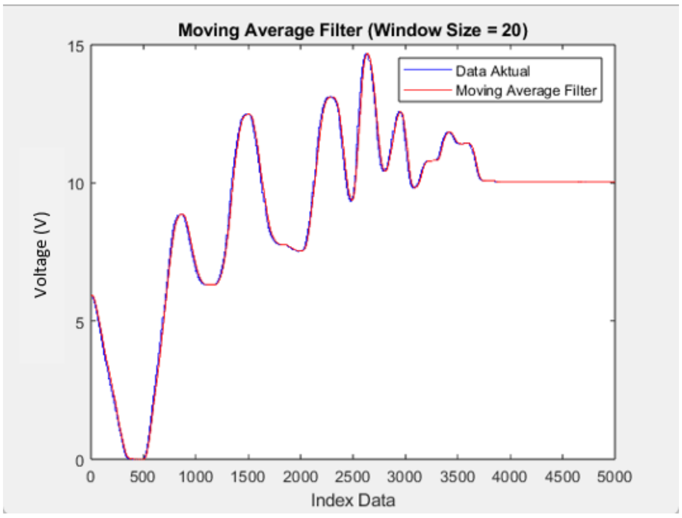

Figure 11. Moving Average result with Window Size=20.

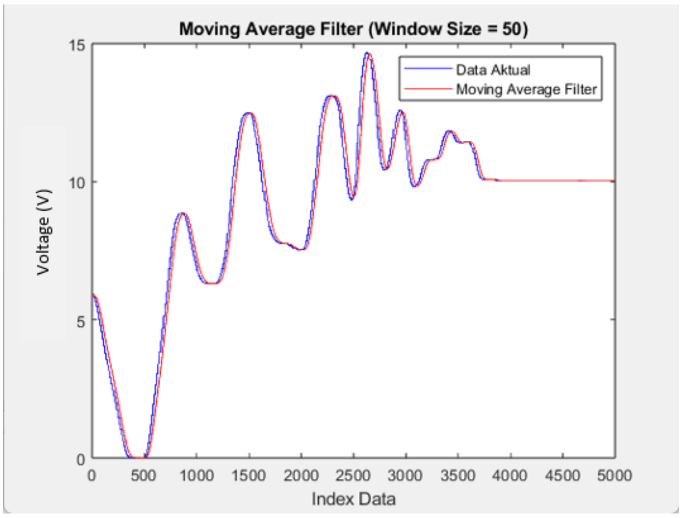

Figure 12. Moving Average result with Window Size=50.

technique utilizing a window size of 20. The graph indicates that the filter yields greater smoothing than the graph with a window size of 5.

Furthermore, Figure 12 shows a graph of the results of the mean average filter approach with a window size = 50. The figure shows that the moving average is more capable of smoothing, producing a more stable filter, and minimizing interference more significantly.

Based on observations of the moving average filter evaluation with various window sizes, it can be concluded that the larger the window size, the smoother the filtering results obtained, consistent with findings that larger sample sizes improve stability and accuracy in sensor measurements [3]. With a window size of 50, the filter is effective in reducing noise and producing a more stable signal, according to actual data. A window size of 50 provides a good balance between signal smoothing and maintaining the actual data. If the window size is larger, for example 100 or 200, the filter tends to smooth the signal excessively. Therefore, a window size of 50 offers an optimal balance between signal smoothing and data accuracy, making it the most appropriate choice for this experiment.

4.4 Comparative Analysis of Kalman and Moving Average Filtering Techniques

This section presents a comparison between the Kalman Filter and the Moving Average Filter in terms of their performance in minimizing noise and enhancing the consistency of sensor signal readings. Both techniques are implemented on data acquired from the load cell sensor. The evaluation focuses on the error values produced by each method and assesses how effectively each approach reduces signal variation and improves the precision of the measurements. The

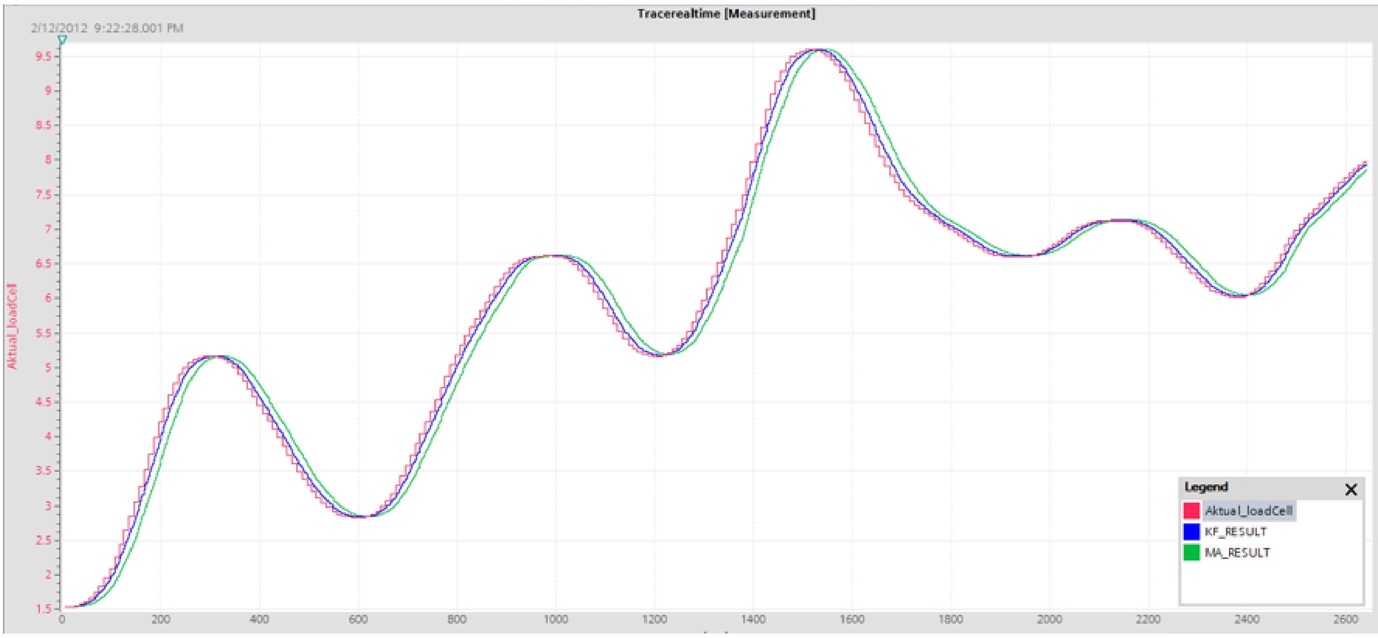

Figure 13. Comparison of Kalman and Moving Average Filters to load cell sensor readings.

objective of this study is to determine which filtering technique provides better optimization of sensor signal readings, thus enhancing the overall data quality in applications that demand high precision and signal stability. The comparative results derived from the application of the Kalman Filter and the moving average filter are presented in Figure 13.

Figure 13 displays the graph resulting from the application of the Kalman Filter using Q = 1 and R = 100, alongside the Moving Average Filter with a window size of 50. The Kalman Filter, represented by the blue line, produces a more refined signal that closely follows the actual data, while still applying a degree of smoothing to minimize noise. Meanwhile, the Moving Average Filter marked in green also follows the actual reading, but the signal is slightly away from the actual value, indicating that it tends to smooth the signal more overall. The original reading value is shown in red, which shows the actual data from the fluctuating load cell sensor. The next step is to integrate the system on the load cell sensor using a Siemens S7-1200 PLC, where these two filter methods will be applied to compare their effectiveness in optimizing the signal reading, with a set point of 5 kg as measurement reference.

Based on Table 2, the average value of the Kalman filter error is smaller than the error without the filter and the moving average filter. The Kalman filter has an average error of 0.0236, which is a little less than the 0.0238 error produced by the moving average filter and the 0.0244 error observed without any filtering. This finding shows that the Kalman Filter is more effective in reducing noise in measurements made at a set point of 5 kg.

Table 2. Comparison of load cell reading error values with a set point of 5kg.

Exp.	Unfiltered (%)	KF (%)	MAF (%)
1	0.012	0.012	0.012
2	0.005	0.005	0.005
3	0.017	0.017	0.017
4	0.007	0.007	0.007
5	0.013	0.012	0.012
6	0.02	0.02	0.019
7	0.01	0.008	0.01
8	0.086	0.085	0.086
9	0.029	0.029	0.028
10	0.045	0.041	0.042
Average	**0.0244**	**0.0236**	**0.0238**

An average error of 0.0244 was recorded in the unfiltered data, suggesting that, in the absence of any filtering technique, the sensor signal is significantly influenced by noise. This leads to unstable and less reliable readings when measuring at the 5 kg reference point. Meanwhile, the Kalman filter resulted in a lower mean error of 0.0236, highlighting its stronger performance in suppressing signal noise and improving estimate accuracy. This method produces more consistent data that align more closely with the expected set point of 5 kg. In contrast, the moving average filter recorded a slightly higher average error of 0.0238, but still effectively reduced noise and provided stable readings at the same reference value. Although it is marginally less precise than the Kalman Filter, it continues to perform well in smoothing out fluctuations in the sensor data.

Although the difference in performance between the Kalman Filter and the Moving Average Filter is relatively small, the Kalman Filter is more effective in improving measurement accuracy and minimizing noise at a set point of 5 kg. As a result, it proves to be the most reliable approach for improving both the accuracy and consistency of sensor measurements compared to the moving average method or unfiltered data.

5 Conclusion

Some limitations in this study include: the maximum capacity of the load cell used is 30 kg, not focusing on the mechanical calculations of the system but focusing on the performance test of the moving average filter and Kalman filter methods. The potential development of this system can be directed by adding a self-calibration feature to the load cell sensor so that the reading accuracy can be maintained periodically without requiring manual adjustments. Thus, this innovation supports the automation of the calibration process and reduces the dependence on operators. The assessment results indicate that the Kalman Filter is superior in enhancing the stability and accuracy of the signal readings from the load cell sensor utilized for simulation. The Kalman Filter, exhibiting an average error of 0.0236, demonstrated superior efficacy in noise reduction and signal fluctuation minimization relative to the unfiltered condition, which yielded an error of 0.0244. However, the moving average filter exhibited a somewhat elevated average error of 0.0238. Despite its commendable performance, this filter exhibited reduced efficiency in managing elevated noise levels. The Kalman Filter has shown superior efficacy in enhancing measurement reliability, making it a more appropriate option for applications that require consistent and high-precision sensor data.Consequently, the Kalman filter can be utilized for an uncertain planning system, and to enhance the accuracy of future system readings, we will employ the extended Kalman filter.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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